Certainty preference, random choice, and loss aversion*

A comment on "Violence and Risk Preference: Experimental Evidence from Afghanistan"

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Abstract

I revisit recent evidence uncovering a 'preference for certainty' in violation of dominant normative and descriptive theories of decision-making under risk. I show that the empirical findings are potentially confounded by systematic noise. I then develop choice lists that allow to disentangle these different explanations. Experimental results obtained with these lists reject explanations based on a 'preference for certainty' in favor of explanations based on random choice. From a theoretical point of view, the levels of risk aversion detected in the choice list involving certainty can be accounted for by prospect theory through reference dependence activated by salient outcomes.

Keywords: risk preferences, certainty effect, random choice, loss aversion;

JEL-classification: C91, D12, D81, O12

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1 Introduction

Risk preferences are central to economic decisions. Nonetheless, the extent to which there exist stable correlates of risk preferences measured in experiments or surveys is still highly debated. Friedman, Isaac, James, and Sunder (2014) recently questioned the usefulness of modeling exercises altogether, arguing that no stable correlates of risk preferences have been found to date. Sutter, Kocher, Glätzle-Rützler, and Trautmann (2013) found no predictive power of experimentally measured risk preferences for the behavior of adolescents. Chuang and Schechter (2015) called into question the stability of risk preferences measured experimentally or through surveys based on low inter-temporal stability and inconsistencies in correlations.

Noise may play a central role in this debate (Hey and Orme, 1994; von Gaudecker, van Soest, and Wengström, 2011; Choi, Kariv, Müller, and Silverman, 2014). Random switching in choice lists may even result in correlations of opposite signs being estimated depending on the design of a list. Andersson, Tyran, Wengström, and Holm (2016) showed forcefully how different choice list designs could result in a negative or a positive correlation of risk aversion with cognitive ability, depending on where the point of risk neutrality falls in a choice list. This insight may be particularly important when participants are distracted, illiterate, or unaccustomed to abstract tasks. A further issue in this debate may be the modeling of preferences, since model mis-specifications could further add to noise in measured preferences.

Investigating risk preferences and their linkage to violence, Callen, Isaqzadeh, Long, and Sprenger (2014) found important interaction effects between how preferences are measured and their empirical correlates. Subjects were found to be less risk averse in a task involving repeated choices between two lotteries than in a task involving choices between a lottery and a sure amount of money. This difference was found to be amplified by fear priming, and by its interaction with exposure to violence. The authors explain this phenomenon by a *preference for certainty*. Such a preference for certainty cannot be accommodated by expected utility theory (EUT; von Neumann and Morgenstern, 1944). What is more, the authors concluded that it also contradicts prospect theory (PT; Kahneman and Tversky, 1979; Tversky and Kahneman, 1992)—the dominant descriptive theory of decision making under risk today (Starmer, 2000; Wakker, 2010).[1]

[1]A number of prospect theory violations have been catalogued to date, although none as fundamental

The account proposed by Callen et al. (2014) suffers from two confounds. The first is empirical, and derives from the observation that some participants may switch at random points in a choice list. I show that such random switching always leads to the observed choice pattern in the setup used, thus constituting a confound for the supposed 'preference for certainty'. I then devise a choice list in which the explanation proposed by Callen et al. (2014) still predicts a preference for certainty, while the random choice model predicts the *opposite* pattern, implying a 'preference for *un*certainty'. While I replicate the preference for certainty using the original choice lists (both with hypothetical tasks as in the original setup and with real incentives), a 'preference for uncertainty' is found with the new choice list. This constitutes direct evidence against a 'preference for certainty' and in favor of a random choice explanation.

The second confound affects the theoretical explanation. Callen et al. (2014) claim that their 'preference for certainty' contradicts both EUT and PT. I show that their PT prediction is conceptually problematic, and that—even if one were willing to take it at face value—it is based on Yaari's (1987) dual-EU theory rather than on PT. This leaves a theoretical vacuum on the correct PT prediction, which I fill based on a classic model first proposed by Hershey and Schoemaker (1985). I show that PT indeed *predicts* the type of choice pattern observed based on reference dependence relative to salient outcomes. I then test the empirical relevance of that model to the setup studied. Using a task in which the sure outcome is varied instead of the probability of winning in the lottery (Tversky and Kahneman, 1992; Bruhin, Fehr-Duda, and Epper, 2010; Abdellaoui, Baillon, Placido, and Wakker, 2011), I show that the task involving a fixed certain outcome over-estimates risk aversion. This indicates that a model incorporating reference-dependence and loss aversion is needed to account for the strong risk aversion found in that task (Rabin, 2000; Köbberling and Wakker, 2005).

2 Original setup and results

I represent binary prospects as $(x, p; y)$, (x, p) when $y = 0$, where $\{x, y\} \in \mathbb{R}$ are monetary outcomes, and $p \in [0, 1]$ is the objectively known probability of obtaining x, with y

as this one. Notable violations include large scale violations of non-transparent first order stochastic dominance (Birnbaum, 1999), contradictions of gain-loss separability for mixed prospects (Baltussen, Post, and van Vliet, 2006; Wu and Markle, 2008), and violations of probability-outcome separability (Fehr-Duda, Bruhin, Epper, and Schubert, 2010).

obtaining with a complementary probability of $1 - p$. I discuss preference relations $\sim$, symbolizing indifference. The dimension varied in a task to obtain indifference is highlighted in bold, and the list from which the preference relation has been obtained is marked by subscripts to the elicited parameters and the derived functions.

Callen et al. (2014) used two elicitation tasks. Both rely on choice lists, varying the probability of winning a prize to obtain a switching point. The first task, shown in panel 1(a), compares two non-degenerate prospects, where $x > y > 0$. Risk preferences are identified by obtaining indifference between the two prospects by varying the probability p_u. The left-hand side prospect in panel 1(a) is riskier than the 50-50 prospect it is compared with. For small probabilities of winning x, one would thus expect a preference for the 50-50 prospect. At some probability level, subjects ought to switch to the riskier prospect on the left, with the switching point carrying interval information about a subject's risk preference. The tradeoff depicted in panel 1(b) is similar, except that the probability is now varied to obtain the point of indifference between playing the prospect and *a sure amount* y. I shall refer to the equivalence obtained in 1(a) as an *uncertainty equivalent (UE*, subscripted by u), in keeping with the authors' terminology. I shall call the measure obtained using the setup in 1(b) a *probability equivalent (PE*, subscripted by p), in keeping with the previous literature (Hershey, Kunreuther, and Schoemaker, 1982).

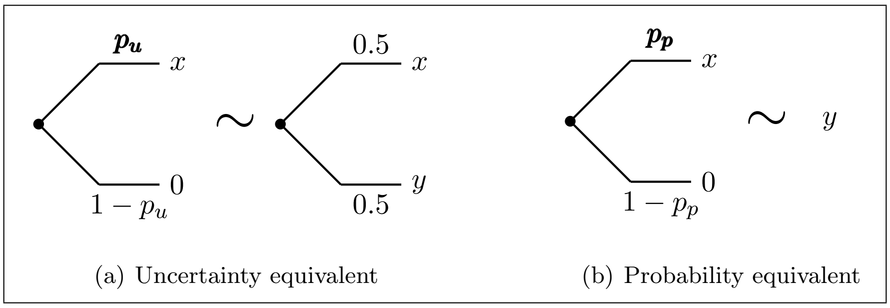


Figure 1: Elicitation tasks under uncertainty (left) and certainty (right)

This setup can be used for nonparametric comparisons of risk preferences across the two tasks under EUT. Let us start from the uncertainty equivalent. Switching points up to and including $p_u = 0.5$ violate first order stochastic dominance. The difference of $p_u - 0.5$, on the other hand, can be taken as a measure of risk aversion. Under EUT we can write the indifference as $p_u u(x) + (1 - p_u)u(0) = 0.5u(x) + 0.5u_u(y)$. Since utility is only unique up to a positive linear transformation, we can set $u(0) = 0$ and $u(x) = 1$ to obtain:

$$u_u(y) = \frac{p_u - 0.5}{0.5} \tag{1}$$

A larger value of $u_u(y)$ indicates increased risk aversion. This can now be directly compared to y/x to determine a subject's risk preference, whereby $u_u(y) > y/x$ indicates risk aversion, $u_u(y) < y/x$ risk seeking, and $u_u(y) = y/x$ risk neutrality.

Next, let us take a look at the indifference elicited from the probability equivalent. This can be represented as $p_p u(x) + (1 - p_p)u(0) = u_p(y)$. After normalizing we obtain

$$u_p(y) = p_p. \tag{2}$$

These two utility values can now be used to test the predictions of different theories. Under EUT, the two methods ought to result in identical estimates, so that $u_u(y) \overset{\text{EUT}}{\equiv} u_p(y)$. This has the directly testable implication that $(p_u - 0.5)/0.5 = p_p$.

For non-EUT theories, the authors construct a 'certainty premium', $\pi = u_p(y) - u_u(y)$. According to the authors, PT then predicts a *negative* certainty premium based on typical probability distortions. The procedure used to arrive at this prediction deserves some attention. They start by assuming linear utility and a probability weighting function $w(p)$ mapping probabilities into decision weights, such that the UE choice can be represented as $w(p_u)x = w(0.5)x + (1 - w(0.5))y$. Solving for the switching probability they obtain

$$\hat{p}_u = w^{-1}\left[\frac{w(0.5)x + (1 - w(0.5))y}{x}\right], \tag{3}$$

where the 'hat' on the probability serves to remind us that this is a predicted value. They then take this predicted switching probability and substitute it into equation 1, derived from an EUT model assuming *nonlinear utility* and *linear probabilities*, to obtain

$$\hat{u}_u(y) = \frac{\hat{p}_u - 0.5}{0.5} = \frac{w^{-1}\left[\frac{w(0.5)x + (1 - w(0.5))y}{x}\right] - 0.5}{0.5}, \tag{4}$$

where the 0.5 probabilities of the comparison prospect are treated again linearly in accordance with EUT. This shift between different theories creates issues of circularity in the argument, and seems mathematically questionable. For instance, in the expression above $\hat{u}_u(y)$ is defined through a probability distortion applied to an expression into which y itself, the utility of which they want to define, enters linearly. This derives from the fact that they use the same equation twice—once to derive EUT expressions, and subsequently to derive 'PT' expressions which they substitute back into the former. This is not the only issue with their formulation. In their footnote 10, Callen et al. (2014) state that they "abstract away from loss aversion around a fixed reference point". Notice, however, that if loss aversion is taken out of the theory, the authors actually do not derive any predictions in terms of PT (they do not have any losses either), but rather in terms of dual-EU theory (Yaari, 1987; i.e. rank-dependent utility with linear utility). I will return to the issue of preference modeling under PT in section 3.

Assuming a probability weighting function $w(p) = {p^\gamma}/{(p^\gamma+(1-p)^\gamma)^{1/\gamma}}$, as originally proposed by Tversky and Kahneman (1992), and using the latter's estimate of $\gamma = 0.61$, they then calculate a *utility value* of $\hat{u}_u(y) = 0.62$, which is compared to a utility of $\hat{u}_p(y) = \hat{p}_p = w^{-1}({y}/{x})$. Since in their choice lists ${y}/{x} = {150}/{450} = {1}/{3}$, and since probability weighting does not generally distort probabilities around ${1}/{3}$ by much, they conclude that PT predicts a *negative* certainty premium. Their findings, however, indicate a *positive* certainty premium, with $u_u(y) = 0.26 < u_p(y) = 0.62$ ($se = 0.01$ for both), so that $\pi > 0$. The authors thus conclude that the results contradict both EUT and PT, indicating a substantial 'preference for certainty'.[2] It is then suggested that this decision pattern is best accounted for by theories incorporating a specific preference for certainty, such as *u*-*v* theory (Neilson, 1992; Schmidt, 1998; Diecidue, Schmidt, and Wakker, 2004) or disappointment aversion (Bell, 1985; Loomes and Sugden, 1986; Gul, 1991).

The distinguishing characteristic of *u*-*v* theory consists in adopting two different utility functions for outcomes obtaining from uncertainty and for certain outcomes. This makes it ideally suited to capture a preference for certainty (indeed, one motivation for it is that it can explain the certainty effect underlying behavior in the Allais paradox more simply than PT; see Diecidue et al., 2004). Away from certainty, the theory behaves like EUT, and the reliance on two different utility functions makes it eminently tractable. A potential disadvantage is that it requires relinquishing fundamental ra-

[2]'Preferences for certainty' are reminiscent of a recent debate in the literature on the effect of risk on time discounting. Andreoni and Sprenger (2012) postulated a disproportionate 'preference for certainty' in such choices, which according to the authors could neither be accommodated by EUT nor by PT. This conclusion was later shown to be driven by a questionable assumption about the state space (Epper and Fehr-Duda, 2015), and by the possibility of hedging inherent in the experimental design (Miao and Zhong, 2015).

tionality principles such as transitivity (Bleichrodt and Schmidt, 2002) or first order stochastic dominance (Diecidue et al., 2004). This is often considered undesirable from the viewpoint of maintaining mathematical tractability (Fehr-Duda and Epper, 2012). Disappointment aversion does not *per se* require abandoning such fundamental principles (although some versions do). While the details differ according to the version of the theory, disappointment from low outcomes only applies in lotteries, which can explain the preference for certainty when a lottery is juxtaposed with a sure outcome.[3]

There are a number of things that are remarkable about the finding. For one, $u_u(y) = 0.26$ falls short of the risk neutrality benchmark $y/x = 0.33$, thus indicating significant risk seeking. This may seem surprising at first, but is in line with the results from recent cross-country comparisons finding risk seeking in developing countries with both students (L'Haridon and Vieider, 2016), and in representative samples (Vieider, Beyene, Bluffstone, Dissanayake, Gebreegziabher, Martinsson, and Mekonnen, 2016). What is more troubling is that the latter studies all used choice lists comparing a binary prospect to sure amounts of money. A 'preference for certainty' such as pointed out be Callen et al. (2014) would lead us to expect strong risk aversion using such tasks. While these studies varied the sure amount of money within a list to obtain indifference instead of eliciting the switching probability, this modification does not affect the explanation proposed by the authors. This further suggests that something other than a 'preference for certainty' may be driving their results.

3 Robustness of results: theory and evidence

I now further explore the results obtained by Callen et al. (2014). The purpose is not to provide a better account of the original data, but rather to point out some specific shortcomings in the authors' analysis. I start from a replication of the original results, using

[3]This is easily shown for the two choice lists discussed above. Without loss of generality, let us assume the version proposed by Loomes and Sugden (1986). Disappointment (and elation) may now arise from the outcomes of a prospect relative to its expected utility. Let the expected utility of a prospect $(x, p; y)$ under EUT be designated by $eu \equiv pu(x) + (1 - p)u(y)$. The utility of this prospect applying disappointment aversion will now be $p[u(x) + D(u(x) - eu)] + (1 - p)[u(y) + D(u(y) - eu)]$, where $D(.)$ is a real-valued function assigning disappointment and elation. To capture the fundamental intuition that disappointment is a more powerful motive than elation, it is typically assumed that $-D(-z) > D(z)$. If this asymmetry is sufficiently strong, disappointment as incorporated in $D(u(y) - eu) = -D(eu - u(y))$ will then weigh down the overall valuation of the prospect relative to its EUT value. This would predict high levels of inferred risk aversion in the PE list, where no disappointment applies to the sure outcome y the prospect is compared with. In the UE list, on the other hand, disappointment aversion would apply to both prospects being compared. This then results in a prediction of higher levels of risk aversion in the PE list than in the UE list, and thus in a positive certainty premium.

both hypothetical tasks as in the original study, and incentivized tasks. I then derive new theoretical predictions pointing to a confound of the original results. I subsequently test these alternative predictions with 1089 subjects in a rural district of Karnataka state, India. Households are sampled from 24 villages that had previously been randomly selected from a district. Participants within a household were selected using a Kish grid (Kish, 1949). Further details of the tasks will be provided as the argument progresses, and the experimental questionnaire can be found in the online appendix.

Replication: hypothetical versus real incentives

The need for testing the stability of the results to monetary payments was explicitly pointed out by the authors (p. 131). I thus ran a hypothetical payoff condition with a small, randomly selected sub-sample ($N = 224$), as well as a real incentive condition ($N = 865$). The two choice lists are shown in figure 2. In addition to the payment, the choice tasks in the real payment condition were represented physically, by laying out the monetary amounts next to the probabilities, which were visualized using colored balls so that no probabilities were mentioned. Probabilities increased within the list in steps of 0.1 from 0 to 1, as in the original setup. While the choice lists shown are similar to those used by Callen et al. (2014), the choice lists used in the real incentive condition also included a line offering a 0 probability of the higher outcome. This line was inserted to obtain an additional test of comprehension.

Task 1: Probability equivalent

	Option A	Choice		Option B
		A	B	
0	**0%** chance of 450 Rs, 100% chance of 0 Rs	O	O	150 Rupees for sure
1	**10%** chance of 450 Rs, 90% chance of 0 Rs	O	O	150 Rupees for sure
2	**20%** chance of 450 Rs, 80% chance of 0 Rs	O	O	150 Rupees for sure
3	**30%** chance of 450 Rs, 70% chance of 0 Rs	O	O	150 Rupees for sure
4	**40%** chance of 450 Rs, 60% chance of 0 Rs	O	O	150 Rupees for sure
5	**50%** chance of 450 Rs, 50% chance of 0 Rs	O	O	150 Rupees for sure
6	**60%** chance of 450 Rs, 40% chance of 0 Rs	O	O	150 Rupees for sure
7	**70%** chance of 450 Rs, 30% chance of 0 Rs	O	O	150 Rupees for sure
8	**80%** chance of 450 Rs, 20% chance of 0 Rs	O	O	150 Rupees for sure
9	**90%** chance of 450 Rs, 10% chance of 0 Rs	O	O	150 Rupees for sure
10	**100%** chance of 450 Rs, 0% chance of 0 Rs	O	O	150 Rupees for sure

Task 2: Uncertainty equivalent

	Option A	Choice		Option B
		A	B	
0	**0%** chance of 450 Rs, 100% chance of 0 Rs	O	O	50% chance of 450 Rs, 50% chance of 150 Rs
1	**10%** chance of 450 Rs, 90% chance of 0 Rs	O	O	50% chance of 450 Rs, 50% chance of 150 Rs
2	**20%** chance of 450 Rs, 80% chance of 0 Rs	O	O	50% chance of 450 Rs, 50% chance of 150 Rs
3	**30%** chance of 450 Rs, 70% chance of 0 Rs	O	O	50% chance of 450 Rs, 50% chance of 150 Rs
4	**40%** chance of 450 Rs, 60% chance of 0 Rs	O	O	50% chance of 450 Rs, 50% chance of 150 Rs
5	**50%** chance of 450 Rs, 50% chance of 0 Rs	O	O	50% chance of 450 Rs, 50% chance of 150 Rs
6	**60%** chance of 450 Rs, 40% chance of 0 Rs	O	O	50% chance of 450 Rs, 50% chance of 150 Rs
7	**70%** chance of 450 Rs, 30% chance of 0 Rs	O	O	50% chance of 450 Rs, 50% chance of 150 Rs
8	**80%** chance of 450 Rs, 20% chance of 0 Rs	O	O	50% chance of 450 Rs, 50% chance of 150 Rs
9	**90%** chance of 450 Rs, 10% chance of 0 Rs	O	O	50% chance of 450 Rs, 50% chance of 150 Rs
10	**100%** chance of 450 Rs, 0% chance of 0 Rs	O	O	50% chance of 450 Rs, 50% chance of 150 Rs

Figure 2: Choice lists for the probability equivalent (top) and uncertainty equivalent (bottom)

Enumerators were extensively trained on these tasks by the author, and had the possibility to practice in several pilot sessions over the course of a week. The enumerators were instructed to go through an example with the subjects. This served to explain all the procedures in detail, and to maximize the probability that participants would understand the tasks. Once the tasks had been run, one of the choices was randomly selected for real payout—the standard procedure in this type of task. The experiments were run in individual interviews at subjects' homes using paper and pencil, and as in Callen et al. (2014) the order of the tasks was fixed. Stakes are very close to those used by the authors. At the time of writing, 1 Afghani corresponded to about 0.015 USD. Converting 450 Afghani to Indian Rupees, we obtain 439 Rupees. I rounded this to 450 Rs for the highest outcome, so that I use nominally identical amounts to the ones used by the authors. This corresponds to about two daily wages for a male farm laborer. In terms of average income the payoffs are much higher than that, since jobs paying such wages are not readily available.

The original patterns are clearly replicated in the hypothetical experiment, with $u_p(y) = 0.49 > u_u(y) = 0.35$ ($z = 5.25, p < 0.001$; signed-rank test[4]), resulting in a positive certainty premium of $\pi = 0.14$. While there is significant risk aversion in the PE list ($z = 5.90, p < 0.001$), risk neutrality cannot be rejected in the UE list ($z = -0.08, p = 0.93$). This corresponds closely to the original findings. The results obtained using real incentives are qualitatively similar, with $u_p(y) = 0.53 > u_u(y) = 0.33$ ($z = 15.89, p < 0.001$), resulting in a certainty premium of $\pi = 0.20$. Although the average $u_u(y)$ falls right on the point of risk neutrality, using a non-parametric signed-rank test I find significant risk seeking with UEs ($z = -2.09, p = 0.037$)[5], confirming the finding by Callen et al. (2014). The PE is furthermore significantly larger under real incentives than in the hypothetical condition ($z = 2.13, p = 0.033$), indicating increased risk aversion. There is no significant effect of the payment condition on the UE ($z = -0.46, p = 0.64$).

A much greater difference between hypothetical and real tasks occurs in terms of rationality violations, such as multiple switching and violations of monotonicity. Multiple switching is rare in the real incentive condition at below 0.5% in both tasks. It is

[4]All test results reported below are based on signed-rank tests when comparing a value to a fixed reference value or to a different utility; tests between treatments or conditions are based on Mann-Whitney tests; all test results are stable to using parametric t-tests instead, unless otherwise specified.

[5]This significant result in conjunction with the mean falling directly on the point of risk neutrality suggests skewness in the distribution of responses. A table reporting summary statistics for the different choice lists is presented in the online appendix.

significantly more frequent in the hypothetical condition, at close to 10% in both tasks (difference significant at $p < 0.001$ in both cases). These differences could be driven either by the incentives provided or by the more detailed explanations in the real incentive condition. I also observe similar differences in terms of monotonicity violations between conditions. These run at about 1% for the PE in the real incentive condition, but are significantly higher at about 7% in the hypothetical condition ($z = -5.03, p < 0.001$). Monotonicity violations are much more frequent in the UE task, where they stand at close to 10% in the real incentive condition, and at over 30% in the hypothetical condition ($z = -8.54, p < 0.001$). Such violations will be excluded from the following analysis. In keeping with the analysis by Callen et al. (2014), I will include instances where $u(y) = 0$, even though this violates monotonicity, in order to maintain comparability of results.[6]

Random choice and preference estimation

Callen et al. (2014) found a remarkable similarity in switching points in their two choice lists. Fully 69% of participants switched at exactly the same point in both lists (after excluding subjects who switched multiple times or who violated monotonicity).[7] This is all the more surprising since such equal switching points entail radically different risk preferences across lists. One way to organize these results is to assume that some subjects exhibit a tendency to switch towards the middle of the list or at random, regardless of the risk preference this entails.[8] Revisiting the relationship between cognitive ability and risk taking, Andersson et al. (2016) demonstrated forcefully how locating the point of risk neutrality at different places in a choice list could result in opposite estimates of the correlation. Asymmetric lists biased towards the detection of risk aversion resulted in an estimated *negative* correlation between risk aversion and cognitive ability. Asymmetric lists biased towards the detection of risk seeking resulted in an estimated *positive*

[6] To be exact, these are instances where subjects switch to preferring the riskier prospect at $p = 0.5$. The assumption is then that the value $p = 0.5$ exactly produces indifference between the two prospects, i.e. that the actual switching point does not lie in the interior of the probability interval between 0.5 and 0.4 (a rather bold assumption). Fully 135 out of the 816 subjects included in the final sample by Callen et al. (2014), or 16.5%, switch at this point in the UE task. In my own sample, about 10% switch at this point in the real incentive condition, and about 15% in the hypothetical condition.

[7] In my own data, I find 25% of subjects switching at exactly the same point in the hypothetical condition, and 21% in the real condition.

[8] Callen et al. (2014) provide a discussion of decision errors in section II.C. They dismiss the relevance of errors based on the observation that they cannot reject the hypothesis that mutliple switching behavior and monotonicity violations are equal for the fear prime and alternative primes, as well as for the fear times violence interaction. This points to some heterogeneity across these dimensions that goes beyond elementary rationality violations. I do not address this heterogeneity here. The point I make is more general and regards the very existence of the postulated 'preference for certainty'.

correlation between risk aversion and cognitive ability.

Callen et al. (2014) fixed the two nonzero outcomes in the choice lists such that $y/x = 1/3$. With the equality point in expected value thus located at $p = 2/3$ in the UE list, and at $p = 1/3$ in the PE list, purely random choice would result in risk seeking in the UE list, and risk aversion in the PE list. Imagine that some subjects switch at a random point in the list (a tendency to switch towards the middle compounds this issue). On average, such behavior will result in an estimate of $p_p = p_u = 0.55$ in both lists. Purely random choice will thus result in a prediction of $u_u(y) = (p_u - 0.5)/0.5 = 0.1 < y/x = 1/3$ in the UE list, indicating risk seeking. The same choice pattern in the PE list will result in $u_p(y) = p_p = 0.55 > 1/3$, indicating risk aversion. Pure random switching would thus result in a positive certainty premium—a finding undistinguishable from the one observed, and thus a confound of a 'preference for certainty'.

I now propose a simple model to account for random choice. Assume that there are two types of subjects. Subjects who correctly identify their true preference regardless of where it falls in the list, which I will characterize by the usual utility functions $u_u(y)$ and $u_p(y)$; and subjects who systematically (or on average) choose a switching point towards the middle of the list. Let ν be the probability that a subject is noisy in the sense just defined. We can model preferences measured in the UE list as follows:

$$\tilde{u}_u(y) = (1 - \nu)u_u(y) + \nu\mu_u, \tag{5}$$

where $\tilde{u}_u(y)$ represents observed utility, and μ_u represents the utility estimated purely from switching in the middle of the list. At $\mu_u = (0.55 - 0.5)/0.5 = 0.1 < 0.33$, random switching implies substantial risk *seeking*. Assume that a subject group is truly moderately risk averse. Then any random choice in the UE list will bias the results towards risk seeking. The higher the proportion of noisy individuals ν, the higher the risk seeking propensity estimated. Preferences in the PE list can be modeled similarly:

$$\tilde{u}_p(y) = (1 - \nu)u_p(y) + \nu\mu_p, \tag{6}$$

where μ_p indicates preferences estimated from switching in the middle of the PE list. This now implies $\mu_p = 0.55 > 0.33$, and thus risk aversion. If true preferences are slightly risk averse, then the random choosers will now bias the measured preferences towards stronger risk aversion. Notice furthermore that, given the permissible ranges of the two choice lists, any type of random choice behavior will result in a supposed preference for certainty, regardless of the true (and unobserved) risk preference captured by $u_u(y)$ and $u_p(y)$, when the proportion of noisy subjects ν is sufficiently large.

To disentangle the prediction of a preference for certainty from the one of random choice, one can devise a choice list in which uncertainty and the response mode are maintained, while the prediction of noise is reversed. This is easily achieved by eliciting an indifference $(x, \boldsymbol{p_\ell}) \sim (y; 0.5)$, with the actual choice list shown in figure 3. I shall call this a *lottery equivalent* (*LE*; McCord and de Neufville, 1986) and subscript it by ℓ.[9] Applying the same normalizations as above and rearranging we obtain $u_\ell(y) = {}^{p_\ell}/_{0.5}$. This value can be directly compared to $u_p(y)$, as well as $u_u(y)$. If a preference for certainty drives behavior we ought to expect levels of risk aversion in the LE task similar to those in the UE task, so that $u_\ell(y) < u_p(y)$ and $u_\ell(y) = u_u(y)$.[10] Random switching now predicts $u_\ell(y) > u_p(y)$, due to the cutoff of well-behaved preferences at 0.5 (i.e., the feature of uncertainty equivalents where only the lower half of the list provided information consistent with monotonicity is exactly reversed). This means that the noise model just presented and preference for certainty now make exactly *opposite* predictions.

	Option A	Choice A	Choice B	Option B
0	**0%** chance of 450 Rs, 100% chance of 0 Rs	O	O	50% chance of 150 Rs, 50% chance of 0 Rs
1	**10%** chance of 450 Rs, 90% chance of 0 Rs	O	O	50% chance of 150 Rs, 50% chance of 0 Rs
2	**20%** chance of 450 Rs, 80% chance of 0 Rs	O	O	50% chance of 150 Rs, 50% chance of 0 Rs
3	**30%** chance of 450 Rs, 70% chance of 0 Rs	O	O	50% chance of 150 Rs, 50% chance of 0 Rs
4	**40%** chance of 450 Rs, 60% chance of 0 Rs	O	O	50% chance of 150 Rs, 50% chance of 0 Rs
5	**50%** chance of 450 Rs, 50% chance of 0 Rs	O	O	50% chance of 150 Rs, 50% chance of 0 Rs
6	**60%** chance of 450 Rs, 40% chance of 0 Rs	O	O	50% chance of 150 Rs, 50% chance of 0 Rs
7	**70%** chance of 450 Rs, 30% chance of 0 Rs	O	O	50% chance of 150 Rs, 50% chance of 0 Rs
8	**80%** chance of 450 Rs, 20% chance of 0 Rs	O	O	50% chance of 150 Rs, 50% chance of 0 Rs
9	**90%** chance of 450 Rs, 10% chance of 0 Rs	O	O	50% chance of 150 Rs, 50% chance of 0 Rs
10	**100%** chance of 450 Rs, 0% chance of 0 Rs	O	O	50% chance of 150 Rs, 50% chance of 0 Rs

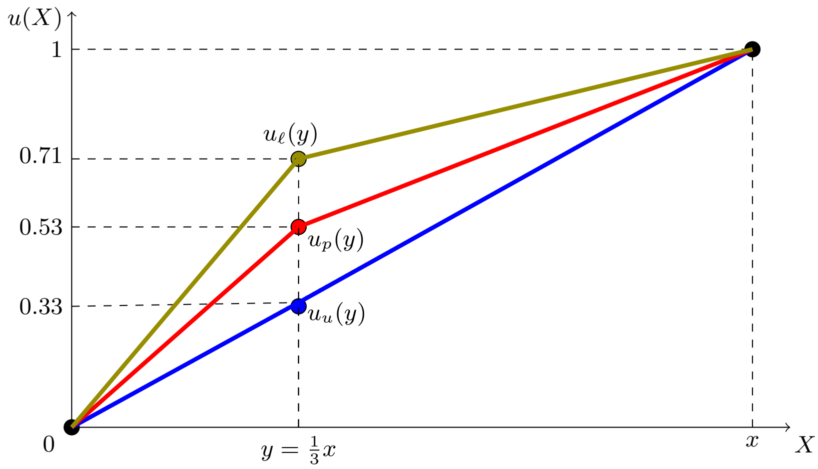
Figure 3: Choice list for the lottery equivalent

[9]LEs were originally introduced by McCord and de Neufville (1986) to address the issue that the concavity of utility functions elicited using certainty equivalents had been found to be increasing in the fixed probability of obtaining the prize when assuming EUT. The disappearance or attenuation of such an effect when both prospects being compared involve uncertainty constitutes an illustration of the well-known common ratio effect, which is an integral part of prospect theory and is captured by the 'certainty effect' (Tversky and Wakker, 1995). Although a common ratio effect around certainty could result in a 'preference for certainty' using the EUT-derived equation of Callen et al. (2014), it actually constitutes one of the classical paradoxes promting the development of prospect theory, which once again illustrates just how problematic the supposed 'PT prediction' derived by the authors is.

[10]The exact prediction may depend on the particular theory adopted to explain the supposed preference for certainty—an issue on which Callen et al. (2014) take no stand. In particular, this prediction holds exactly assuming u-v theory. If one assumes disappointment aversion, the second part of the prediction would be more correctly represented as an approximate equality, $u_\ell(y) \simeq u_u(y)$, with the details depending on the version of the theory and the parameter values adopted. In any case, however, the limiting case as disappointment aversion goes to infinity would be a prediction of $u_\ell(y) \rightarrow u_p(y)$, while the noise account predicts that $u_\ell(y) > u_p(y)$, i.e. we would expect even *more* risk aversion in LEs than detected when eliciting probability equivalents.

The three utility functions obtained with the different lists are depicted in figure 4. Deploying this choice list with the same subjects as above (real incentive treatment only), I find an average utility value in the LE list of $u_\ell(y) = 0.71$. This value is significantly larger than $u_p(y) = 0.53$ ($z = 17.70, p < 0.001$), thus seemingly indicating a 'preference for *uncertainty*' (indeed, there is now a negative certainty premium of $\pi = -0.18$). The difference is even larger when comparing $u_\ell(y)$ to $u_u(y)$ ($z = 19.22, p < 0.001$). Indeed, the PE list involving certainty results in a utility level almost exactly intermediate between the two values obtained with the lists involving only uncertainty. This pattern can clearly not be explained by *u*-*v* theory, since both the UE and LE choice lists now contain only uncertain outcomes. It can also not be explained by disappointment aversion, which now is activated by both lotteries (although potentially to differential degrees—see footnote 10). This pattern is, however, predicted by the random choice model presented above.

Figure 4: Utility functions for PE, UE, and LE



Reference dependence and preference modeling under PT

The evidence presented above shows the importance of noise, but it is not informative about the theoretical issue of preference modeling. Imagine that we could find a positive certainty premium comparing a choice between two non-degenerate prospects and a choice between a prospect and a sure amount of money that are not affected by systematic noise such as described above. Would this mean that PT is automatically rejected? I have shown above that the PT prediction presented by the authors is problematic. This has created a theoretical void around the modeling of the decision situation under PT which holds some interest beyond the empirical case made above, and which I will now attempt to fill. The measured PEs may indeed be affected by response mode effects over and beyond the effects due to noise detailed above. Such response mode effects are suggested by the contrast to the cross-country comparisons using certainty equivalents reported by L'Haridon and Vieider (2016) and Vieider et al. (2016), who found people in developing countries to be relatively risk tolerant.

In a classic investigation, Hershey and Schoemaker (1985) found discrepancies in risk taking between a probability matching task and an outcome matching task when comparing a sure amount of money to a lottery (see also Johnson and Schkade, 1989; Delquié, 1993). They found significantly higher risk aversion in the task varying probabilities compared to a task varying outcomes. They explained this by a shift in the reference point under PT. They observed that "[...] some subjects might reframe the PE question as mixed since in the PE model all dollar amounts are held constant, and attention is focused on the variable probability dimension. Consequently, the gamble's outcomes may be psychologically coded as 'gains' and 'losses' relative to the sure outcome" (p. 1224). PEs may thus lead to an over-estimation of risk aversion due to loss aversion when such reference points are ignored (Rabin, 2000; Köbberling and Wakker, 2005). Callen et al. (2014) did indeed not derive any true PT prediction, given that they "abstract away from loss aversion" (footnote 10) and have no losses, thus rather deriving a (mathematically questionable) dual-EU prediction (Yaari, 1987).

There is a straightforward way of modeling reference-dependent behavior. Assume there are two types of subjects. Subjects who evaluate the prospect according to EUT as detailed above, which I will characterize by the usual utility function $u_p(y) = p_p$; and a proportion ρ of subjects who adopt the sure outcome y as a reference point when the probability is varied in a choice list. This can be written as:

$$\overline{u}_p(y) = (1-\rho)p_p + \rho\pi, \tag{7}$$

where $\overline{u}_p(y)$ represents the observed utility. With a probability $1-\rho$, this utility is simply equal to $u_p(y)$ and hence to p_p, i.e. it is equal to the probability that makes the prospect (x, p_p) equally attractive as the sure outcome y under EUT. With a probability ρ, however, the value is equal to π, which is a probability elicited to obtain the equality $u(0) = \pi u(x-y) - \lambda(1-\pi)u(y)$, where $\lambda > 1$ indicates loss aversion (and where

I insert probabilities linearly as probability distortions are likely only of second order importance in this instance). This last expression obtains by shifting all outcomes down by the exogenously fixed amount y that can be obtained for sure. The probability π is then elicited such as to equate the value of the reframed prospect to $u(0) = 0$. Since loss aversion significantly increases the weight attributed to the loss part, the elicited π in reframed prospects will generally be larger than p_p to compensate for the disutility of the loss. This leads to an overestimation of risk aversion if reference-dependence is not taken into account. In a recent investigation of the determinants of reference points, Baillon, Bleichrodt, and Spinu (2015) showed that about 31% of subjects fix on such 'max-min' reference points.

The model just described establishes the theoretical PT prediction—even after eliminating noise, we would still expect high risk aversion to be measured from PEs due to loss aversion. I now test whether this theoretical prediction is also borne out empirically, exploiting that increases in risk aversion are only predicted when probabilities are varied within a choice list to obtain indifference, thereby making the sure outcome salient. When the sure outcome is varied in the choice list instead, we would expect no such effect to occur. This can easily be tested by adopting p_p from the PE task to construct a new prospect, and then eliciting a certainty equivalent for that prospect. I thus presented subjects in the real incentive condition with an additional choice list in which the prize x could be obtained with a probability given by the first probability for which they chose the prospect in the PE task.[11] Within the list, the sure amount of money was varied in 10 equal steps between 0 and 450 to obtain a certainty equivalent (CE, subscripted by c). This choice list is shown in figure 5.

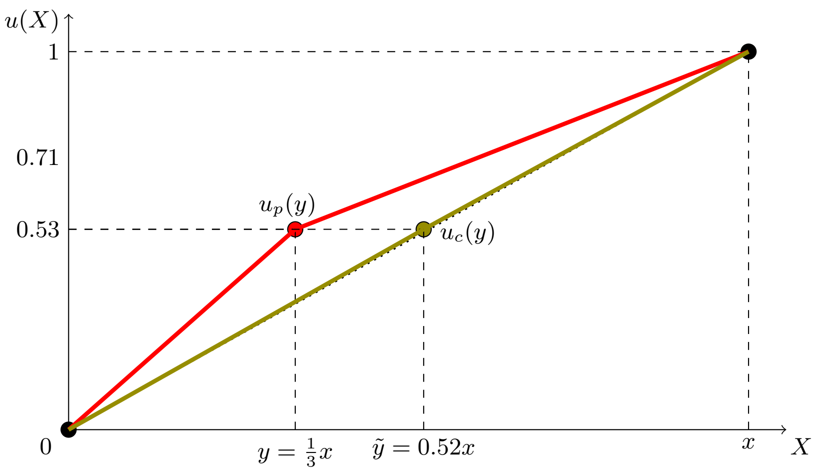
	Option A	**Choice**		**Option B**
		A	**B**	
0	[p_p]% chance of 450 Rs, [1-p_p] % chance of 0 Rs	O	O	**0** Rupees for sure
1	[p_p]% chance of 450 Rs , [1-p_p] % chance of 0 Rs	O	O	**45** Rupees for sure
2	[p_p] % chance of 450 Rs, [1-p_p] % chance of 0 Rs	O	O	**90** Rupees for sure
3	[p_p] % chance of 450 Rs, [1-p_p] % chance of 0 Rs	O	O	**135** Rupees for sure
4	[p_p]% chance of 450 Rs, [1-p_p] % chance of 0 Rs	O	O	**180** Rupees for sure
5	[p_p] % chance of 450 Rs, [1-p_p] % chance of 0 Rs	O	O	**225** Rupees for sure
6	[p_p] % chance of 450 Rs, [1-p_p] % chance of 0 Rs	O	O	**270** Rupees for sure
7	[p_p] % chance of 450 Rs, [1-p_p] % chance of 0 Rs	O	O	**315** Rupees for sure
8	[p_p] % chance of 450 Rs, [1-p_p] % chance of 0 Rs	O	O	**360** Rupees for sure
9	[p_p]% chance of 450 Rs, [1-p_p] % chance of 0 Rs	O	O	**405** Rupees for sure
10	[p_p]% chance of 450 Rs, [1-p_p] % chance of 0 Rs	O	O	**450** Rupees for sure

Figure 5: Choice list lottery equivalent (p_p: first probability for which prosepct was chosen in PE list)

[11] This procedure was applied only to subjects with well-behaved preferences, i.e. who did not switch multiple times or violate monotonicity. In the latter cases, no well-defined or non-degenetare probability could be obtained from the choice, and enumerators were explicitly instructed to skip this choice list.

If there is no reference-dependence, we ought to observe $\tilde{y} = y$, where $\tilde{y}$ is the sure amount of money indicating indifference. Reference-dependence predicts $\tilde{y} > y$, representing lower risk aversion for CEs than for PEs.[12] I find $\tilde{y} = 235.55 > y = 150$ ($z = 16.19, p < 0.001$). The resulting utility functions are depicted in figure 6. In contrast to the clearly concave pattern found for the PE, utility obtained from the CE is undistinguishable from a pattern of risk neutrality ($z = 0.18, p = 0.86$). Reference dependence thus appears to play a role in explaining choices in the PE list.

Figure 6: Utility functions for PE and CE



This conclusion may still be confounded by random switching. Given the asymmetric setup of the initial PE list, with an expected value switching point at $p_p = {}^{1}\!/_{3}$, the random choice account presented above will also still predict an overestimation of risk aversion. At the same time, that account will predict an overestimation of risk *seeking* in the CE list, since the point of risk neutrality falls again at one third of the list, and higher switching points now indicate *lower* levels of risk aversion.[13] This issue can be easily avoided by making the point of risk neutrality coincide with the middle of the list. I thus used an additional CE list to elicit $\boldsymbol{ce} \sim (x, 0.5)$. I subsequently used the individually obtained ce as an input to a PE list, to elicit $(x, \boldsymbol{p}) \sim y_c$, where y_c indicates the first sure amount chosen over the prospect in the CE list (the lists are

[12] Andreoni and Sprenger (2010) used certainty equivalents instead of probability equivalents in their elicitation. While they do find a positive certainty premium, the latter is an order of magnitude smaller than the one found by Callen et al. (2014). They provide no direct comparison between certainty equivalents and probability equivalents. Several elements vary between the two studies, including the subject pool and response modes, which makes it impossible to disentangle the exact causes of the differences. Response modes have, however, been found to produce strong effects which are consistent with the differences observed—see Delquié (1993) for a systematic investigation.

[13] A similar issue may occur in this case due to so-called Fechner errors, and the chained nature of the tasks. This does not alter my conclusions in any way—see online appendix for a discussion.

similar to the ones above and thus not shown; see online appendix). By preference for certainty, we would expect $p_p = 0.5$, given that both choice lists now involve certainty. Reference dependence, on the other hand, predicts $p_p > 0.5$. Notice how the random choice model now also pushes preferences towards $p_p = 0.5$, so that any 'preference for certainty' would be further reinforced by noise, making this a hard test of reference dependence. Nonetheless, I comfortably reject the null hypothesis of $p_p = 0.5$ in favor of the reference-dependence account, with $p_p = 0.62$ ($z = 13.84, p < 0.001$). I now find a CE of $\hat{y} = 214.75$, which is smaller than the expected value of 225 but indicates only very slight risk aversion ($z = -2.41, p = 0.016$). This further shows that reference dependence is indeed important to account for the data reported by Callen et al. (2014), in addition to the random switching account presented above.

4 Conclusion

Callen et al. (2014) found that risk aversion measured using a probability equivalent, comparing a lottery to a sure outcome, was much stronger than risk aversion measured using what they termed an uncertainty equivalent, comparing two lotteries. From an empirical point of view, this was taken to indicate a 'preference for certainty', whereby people are supposed to be more risk averse whenever an option can be obtained for sure, relative to a situation in which no certain option is available. Theoretically, they concluded that such preferences contradict both expected utility theory and prospect theory, and that they can best be organized by theories incorporating an explicit preference for certainty, such as u-v theory or disappointment aversion.

Empirically, their explanation is confounded by an account based on random switching, which in their setup produces results identical to those predicted by a preference for certainty. I thus developed a choice list that involves only uncertainty, but makes opposite predictions of a preference for certainty based on a the random switching argument. I found this list to produce even higher levels of risk aversion than the probability equivalent list, and much higher risk aversion than the uncertainty equivalent list. This led me to conclude that the original results were indeed driven by noise.

Theoretically, I showed their 'prospect theory prediction' to be problematic. I then proposed an alternative theoretical prediction for probability equivalents derived from a classic result by Hershey and Schoemaker (1985) and relying on reference-dependence in the presence of salient outcomes. I tested this prediction empirically by comparing the probability equivalent to a *certainty equivalent*, where the sure outcome is varied instead of the probability dimension in a choice list. The certainty equivalents obtained indicated much lower levels of risk aversion, with subjects being close to risk neutrality on average. This goes to show that the probability equivalent triggers reference point effects in some participants, so that the high risk aversion observed in that task is mostly driven by loss aversion (Rabin, 2000; Köbberling and Wakker, 2005).

There remains a more general point to be made. Some recent contributions have argued that risk preferences as measured in experiments and surveys perform badly at predicting real world outcomes, and that no stable correlates of risk preferences have been found (Friedman et al., 2014; Chuang and Schechter, 2015). Inconsistent or null results in correlation analysis may well be driven by measurement problems. Measures of risk preferences are well known to be noisy (Hey and Orme, 1994; Loomes, 2005; von Gaudecker et al., 2011; Andersson et al., 2016)—an issue that may be exasperated by low incentives, distraction during the experiment, or low education levels, as well as imperfect measurement techniques. Jointly with model mis-specifications such as the one pointed out in this paper, such issues may underly some of the failures to replicate previously found correlations. More research is clearly needed to obtain a systematic understanding of these issues.

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ONLINE APPENDIX: For online publication only

Stochastic theories of choice

Decisions in experiments are notoriously noisy. Deterministic theories of decision making under risk are thus typically paired with stochastic models describing how noise may influence decision making patterns (Conte, Hey, and Moffatt, 2011; von Gaudecker et al., 2011). I have discussed a very specific type of *systematic* error, consisting in switching towards the middle of a choice list. To model non-systematic errors, three different models are typically used in the literature. The first consists in a fixed probability of making a random error when choosing between prospects, typically referred to as a 'tremble' (Harless and Camerer, 1994). Such errors are especially useful to explain monotonicity violations. Since the latter have largely been excluded from the data and this error structure makes no further predictions for the issues discussed in the paper, I will not further discuss this. The random preference model predicts that preference parameters may be picked at random from a set of preference parameters (Loomes and Sugden, 1995). Again, this error structure makes no differential predictions on the tasks discussed above. Arguably the most commonly used error structure consists in Fechner errors (Hey and Orme, 1994). This deserves some further discussion, as it could in principle account for some of the patterns I described.

Fechner errors may provide an alternative explanation to both the preference for certainty and the reframing explanations. While it is relatively straightforward to design an implementation that is immune to the systematic error explanation formalized in the main text, purely random errors may impact observations due to the chained nature of the tasks when comparing PEs to CEs (Hershey and Schoemaker, 1985; Johnson and Schkade, 1989). Assume that the elicited dimension in step one is observed with some error, i.e. $p_p = \hat{p} + \epsilon_p$ or $y_c = \hat{y} + \epsilon_c$, i.e. there is some randomly distributed error term attached to the observation. Further assume that $\epsilon \sim N(0, \sigma^2)$, i.e. the error is normally distributed with mean zero and variance σ^2 (Hey and Orme, 1994).

I will discuss only the implications for probability equivalents in the interest of brevity, but the second case has similar implications (see Hershey and Schoemaker, 1985, section 5, for a more detailed discussion). Starting from the probability equivalent, the second step will consist in eliciting $y^* \sim (x; p_p)$, i.e. the sure amount of money that makes the decision maker indifferent to playing a prospect offering the switching probability from the PE task at a prize x or else 0. From this, we obtain $y^* = u^{-1}(\hat{p} + \epsilon_p) + \epsilon_c$ by EUT and the usual normalizations. That is, the switching outcome indicating indifference will now contain two disturbance terms. One is a random error that is realized in this new choice list. The other is the error realized in the PE list, which is carried over to this new choice list because of the chained nature of the task.

Now assume a risk neutral decision maker. A first stage response with a negative error will be interpreted as risk seeking, and a response with a positive error as risk averse. This may then result in second stage responses to indicate relatively more risk seeking behavior than in the first stage as found by Hershey and Schoemaker (1985), simply based on the fact that the initial error is 'corrected' (i.e., high risk aversion due to an error in PEs may not be replicated for CEs). Hershey and Schoemaker (1985) excluded such an account on quantitative terms, considering it incompatible with the strength of the effects found (see also the more general results collected by Johnson and Schkade (1989)). In the case presented in this paper, I can fully exclude such a noise account. Indeed, the explanation proposed above creates an issue only when the response mode effects strongly interacts with the initial response (i.e., only subjects who are initially risk averse in the PE list become risk averse in the CE task, and vice versa). This is not the case in the data presented, where these effects hold *on average*, so that Fechner errors cannot account for the results.

Distribution of responses

We have seen in the main text that uncertainty equivalents in the real incentive conditions resulted in the estimation of significant risk seeking based on a nonparametric test, even though the average value fell directly on the point of risk neutrality. This suggest that responses on the choice lists are skewed. Table 1 reports some descriptive statistics on the different choice lists employed, including the mean, median, standard deviation, skewness, kurtosis, minimum and maximum. These measures are based on the measures used in the main text, i.e. excluding multiple switching and monotonicity violations.

Table 1: Descriptive statistics for different choice lists

choice task	mean	median	stand. dev.	skewness	kurtosis	min	max
PE (hyp.)	0.45	0.45	0.26	0.13	2.16	0.05	0.95
UE (hyp)	0.68	0.65	0.15	0.28	2.13	0.45	0.95
PE (real)	0.49	0.55	0.21	-0.28	2.83	0.05	0.95
UE (real)	0.67	0.65	0.13	0.20	2.39	0.45	0.95
$CE(p_p)$	235.55	247.5	116.88	-0.17	2.11	22.5	227.5
LE	0.36	0.45	0.14	-1.25	3.12	0.05	0.45
$CE(0.5)$	214.75	202.5	111.49	-0.08	2.32	22.5	427.5
$PE(\tilde{y})$	0.57	0.55	0.21	-0.39	3.01	0.05	0.95

A Full-lenght instructions (English)

Below we include the full-length instructions in English.

Experimental tasks (please explain each task separately)
We would like to ask you to make some choice that involve trading off different lotteries, or lotteries and sure amounts of money. We will ask you for your choices in several such tasks, each of which may involve several choices. Please consider these tasks carefully and indicate your choices. Once you have taken all the decisions, ***one of our choices will be randomly selected and played for real money***. Paying close attention to all the dimensions of the decision problem is important, inasmuch as it may determine how much money you will win in the end. I will provide you with detailed information on each of the tasks. If you have any questions or doubts, do not hesitate to ask. There are no right or wrong answers, we are only interested in your preferences.

[Instructions for enumerators:] Please explain each of the tasks carefully. In particular, point out whether the comparison is between two lotteries, or between a lottery and a sure amount of money. Also point out what changes within a choice list. Once you are done with the first choice list, write down the first probability for which the participant prefers the lottery (option A) over the sure amount of money (option B). Do so in private, without showing this to the participant. You will need this number in choice problem 3.

Please take care in explaining the probabilities and outcomes involved. Show both outcomes and probabilities physically, using real money and a bag with numbered or coloured balls. Before getting started, show a choice problem between two lotteries, and illustrate how the extraction process will work. Make sure you explain that one choice will be played for real money, and that it is optimal to decide for each choice as if it were the one being played for real. Makes sure participants understand the trade-offs between lotteries before getting started.

Task 1 [*Instructions for enumerators*:] Record the first probability for which option A is chosen and write it down in secret

First, we will ask you a question over an amount for certain, or an amount that will depend on which of ten numbers you draw from a bag. Option A offers you a chance to win 450 Rs or 0 Rs. The probability of winning increases as you move down the list. Option B always gives you Rs 150 for sure.

	Option A	Choice A	Choice B	Option B
0	**0%** chance of 450 Rs, 100% chance of 0 Rs	O	O	150 Rupees for sure
1	**10%** chance of 450 Rs, 90% chance of 0 Rs	O	O	150 Rupees for sure
2	**20%** chance of 450 Rs, 80% chance of 0 Rs	O	O	150 Rupees for sure
3	**30%** chance of 450 Rs, 70% chance of 0 Rs	O	O	150 Rupees for sure
4	**40%** chance of 450 Rs, 60% chance of 0 Rs	O	O	150 Rupees for sure
5	**50%** chance of 450 Rs, 50% chance of 0 Rs	O	O	150 Rupees for sure
6	**60%** chance of 450 Rs, 40% chance of 0 Rs	O	O	150 Rupees for sure
7	**70%** chance of 450 Rs, 30% chance of 0 Rs	O	O	150 Rupees for sure
8	**80%** chance of 450 Rs, 20% chance of 0 Rs	O	O	150 Rupees for sure
9	**90%** chance of 450 Rs, 10% chance of 0 Rs	O	O	150 Rupees for sure
10	**100%** chance of 450 Rs, 0% chance of 0 Rs	O	O	150 Rupees for sure

Task 2

This works like task 1. However, you are now asked to compare two lotteries. Option A is the same as before. Option B now always gives a 50% chance of obtaining 450 Rs and a 50% chance of obtaining 150 Rs. The probability of winning in option A increases as you move down the list.

	Option A	Choice A	Choice B	Option B
0	**0%** chance of 450 Rs, 100% chance of 0 Rs	O	O	50% chance of 450 Rs, 50% chance of 150 Rs
1	**10%** chance of 450 Rs, 90% chance of 0 Rs	O	O	50% chance of 450 Rs, 50% chance of 150 Rs
2	**20%** chance of 450 Rs, 80% chance of 0 Rs	O	O	50% chance of 450 Rs, 50% chance of 150 Rs
3	**30%** chance of 450 Rs, 70% chance of 0 Rs	O	O	50% chance of 450 Rs, 50% chance of 150 Rs
4	**40%** chance of 450 Rs, 60% chance of 0 Rs	O	O	50% chance of 450 Rs, 50% chance of 150 Rs
5	**50%** chance of 450 Rs, 50% chance of 0 Rs	O	O	50% chance of 450 Rs, 50% chance of 150 Rs
6	**60%** chance of 450 Rs, 40% chance of 0 Rs	O	O	50% chance of 450 Rs, 50% chance of 150 Rs
7	**70%** chance of 450 Rs, 30% chance of 0 Rs	O	O	50% chance of 450 Rs, 50% chance of 150 Rs
8	**80%** chance of 450 Rs, 20% chance of 0 Rs	O	O	50% chance of 450 Rs, 50% chance of 150 Rs
9	**90%** chance of 450 Rs, 10% chance of 0 Rs	O	O	50% chance of 450 Rs, 50% chance of 150 Rs
10	**100%** chance of 450 Rs, 0% chance of 0 Rs	O	O	50% chance of 450 Rs, 50% chance of 150 Rs

Task 3 [*Instructions for enumerators:*] *The probability of switching needs to be taken from task 1, take the first preference for option A.*
You are again asked to choose between two options. Option A gives you a fixed chance of ____% at 450 Rs, or else 0 Rs. Option B gives you an amount for sure. As you move down the list, the sure amount of money increases. Please indicate a choice for each line.

	Option A	Choice		Option B
		A	B	
0	_____% chance of 450 Rs, _____% chance of 0 Rs	O	O	**0** Rupees for sure
1	_____% chance of 450 Rs, _____% chance of 0 Rs	O	O	**45** Rupees for sure
2	_____% chance of 450 Rs, _____% chance of 0 Rs	O	O	**90** Rupees for sure
3	_____% chance of 450 Rs, _____% chance of 0 Rs	O	O	**135** Rupees for sure
4	_____% chance of 450 Rs, _____% chance of 0 Rs	O	O	**180** Rupees for sure
5	_____% chance of 450 Rs, _____% chance of 0 Rs	O	O	**225** Rupees for sure
6	_____% chance of 450 Rs, _____% chance of 0 Rs	O	O	**270** Rupees for sure
7	_____% chance of 450 Rs, _____% chance of 0 Rs	O	O	**315** Rupees for sure
8	_____% chance of 450 Rs, _____% chance of 0 Rs	O	O	**360** Rupees for sure
9	_____% chance of 450 Rs, _____% chance of 0 Rs	O	O	**405** Rupees for sure
10	_____% chance of 450 Rs, _____% chance of 0 Rs	O	O	**450** Rupees for sure

Task 4
We now ask you to make a choice between two lotteries. Option A offers a chance at 450 Rs or Rs 0, with a probability of obtaining the prize that increases as you go down the list. Option B always offers a 50% chance at 150 Rs and a 50% chance at 0.

	Option A	Choice		Option B
		A	B	
0	**0%** chance of 450 Rs, 90% chance of 0 Rs	O	O	50% chance of 150 Rs, 50% chance of 0 Rs
1	**10%** chance of 450 Rs, 90% chance of 0 Rs	O	O	50% chance of 150 Rs, 50% chance of 0 Rs
2	**20%** chance of 450 Rs, 80% chance of 0 Rs	O	O	50% chance of 150 Rs, 50% chance of 0 Rs
3	**30%** chance of 450 Rs, 70% chance of 0 Rs	O	O	50% chance of 150 Rs, 50% chance of 0 Rs
4	**40%** chance of 450 Rs, 60% chance of 0 Rs	O	O	50% chance of 150 Rs, 50% chance of 0 Rs
5	**50%** chance of 450 Rs, 50% chance of 0 Rs	O	O	50% chance of 150 Rs, 50% chance of 0 Rs
6	**60%** chance of 450 Rs, 40% chance of 0 Rs	O	O	50% chance of 150 Rs, 50% chance of 0 Rs
7	**70%** chance of 450 Rs, 30% chance of 0 Rs	O	O	50% chance of 150 Rs, 50% chance of 0 Rs
8	**80%** chance of 450 Rs, 20% chance of 0 Rs	O	O	50% chance of 150 Rs, 50% chance of 0 Rs
9	**90%** chance of 450 Rs, 10% chance of 0 Rs	O	O	50% chance of 150 Rs, 50% chance of 0 Rs
10	**100**% chance of 450 Rs, 0% chance of 0 Rs	O	O	50% chance of 150 Rs, 50% chance of 0 Rs

Task 5

You are again asked to choose between two options. Option A gives you a fixed chance of 50% at 450 Rs and a chance of 50% at Rs. 0. Option B gives you an amount for sure. As you move down the list, the sure amount of money increases. Please indicate a choice for each line.

	Option A	**Choice**		**Option B**
		A	**B**	
0	50% chance of 450 Rs, 50% chance of 0 Rs	O	O	**0** Rupees for sure
1	50% chance of 450 Rs, 50% chance of 0 Rs	O	O	**45** Rupees for sure
2	50% chance of 450 Rs, 50% chance of 0 Rs	O	O	**90** Rupees for sure
3	50% chance of 450 Rs, 50% chance of 0 Rs	O	O	**135** Rupees for sure
4	50% chance of 450 Rs, 50% chance of 0 Rs	O	O	**180** Rupees for sure
5	50% chance of 450 Rs, 50% chance of 0 Rs	O	O	**225** Rupees for sure
6	50% chance of 450 Rs, 50% chance of 0 Rs	O	O	**270** Rupees for sure
7	50% chance of 450 Rs, 50% chance of 0 Rs	O	O	**315** Rupees for sure
8	50% chance of 450 Rs, 50% chance of 0 Rs	O	O	**360** Rupees for sure
9	50% chance of 450 Rs, 50% chance of 0 Rs	O	O	**405** Rupees for sure
10	50% chance of 450 Rs, 50% chance of 0 Rs	O	O	**450** Rupees for sure

Task 6

We now ask you to make a choice between two lotteries. Option A offers a chance at 450 Rs or 0 Rs, with a fixed probability of 40% of obtaining the prize. Option B always offers an 80% chance at a prize, which increases as you go down the list, and a 20% chance at 0.

	Option A	**Choice**		**Option B**
		A	**B**	
0	40% chance of 450 Rs, 60% chance of 0 Rs	O	O	80% chance of **0** Rs, 20% chance of 0 Rs
1	40% chance of 450 Rs, 60% chance of 0 Rs	O	O	80% chance of **45** Rs, 20% chance of 0 Rs
2	40% chance of 450 Rs, 60% chance of 0 Rs	O	O	80% chance of **90** Rs, 20% chance of 0 Rs
3	40% chance of 450 Rs, 60% chance of 0 Rs	O	O	80% chance of **135** Rs, 20% chance of 0 Rs
4	40% chance of 450 Rs, 60% chance of 0 Rs	O	O	80% chance of **180** Rs, 20% chance of 0 Rs
5	40% chance of 450 Rs, 60% chance of 0 Rs	O	O	80% chance of **225** Rs, 20% chance of 0 Rs
6	40% chance of 450 Rs, 60% chance of 0 Rs	O	O	80% chance of **270** Rs, 20% chance of 0 Rs
7	40% chance of 450 Rs, 60% chance of 0 Rs	O	O	80% chance of **315** Rs, 20% chance of 0 Rs
8	40% chance of 450 Rs, 60% chance of 0 Rs	O	O	80% chance of **360** Rs, 20% chance of 0 Rs
9	40% chance of 450 Rs, 60% chance of 0 Rs	O	O	80% chance of **405** Rs, 20% chance of 0 Rs
10	40% chance of 450 Rs, 60% chance of 0 Rs	O	O	80% chance of **450** Rs, 20% chance of 0 Rs

Task 7 [Instructions for enumerators:] Insert the first amount for which option B was chosen in task 5 into option B below
Below, we ask you to choose between a lottery and a sure amount. Option A offers you either 450 Rs or else 0 Rs, with a probability of winning that increases as you move down the list. Option B offers you the same sure amount throughout.

	Option A	**Choice**		**Option B**
		A	**B**	
0	**0%** chance of 450 Rs, 90% chance of 0 Rs	O	O	_____ Rupees for sure
1	**10%** chance of 450 Rs, 90% chance of 0 Rs	O	O	_____ Rupees for sure
2	**20%** chance of 450 Rs, 80% chance of 0 Rs	O	O	_____ Rupees for sure
3	**30%** chance of 450 Rs, 70% chance of 0 Rs	O	O	_____ Rupees for sure
4	**40%** chance of 450 Rs, 60% chance of 0 Rs	O	O	_____ Rupees for sure
5	**50%** chance of 450 Rs, 50% chance of 0 Rs	O	O	_____ Rupees for sure
6	**60%** chance of 450 Rs, 40% chance of 0 Rs	O	O	_____ Rupees for sure
7	**70%** chance of 450 Rs, 30% chance of 0 Rs	O	O	_____ Rupees for sure
8	**80%** chance of 450 Rs, 20% chance of 0 Rs	O	O	_____ Rupees for sure
9	**90%** chance of 450 Rs, 10% chance of 0 Rs	O	O	_____ Rupees for sure
10	**100%** chance of 450 Rs, 0% chance of 0 Rs	O	O	_____ Rupees for sure

Task 8
We now ask you to make a choice between two lotteries. Option A offers a chance at 450 Rs or 0 Rs, with a fixed probability of 10% of obtaining the prize. Option B always offers a 20% chance at a prize, which increases as you move down the list, and an 80% chance at 0.

	Option A	**Choice**		**Option B**
		A	**B**	
0	10% chance of 450 Rs, 90% chance of 0 Rs	O	O	20% chance of **0** Rs, 80% chance of 0 Rs
1	10% chance of 450 Rs, 90% chance of 0 Rs	O	O	20% chance of **45** Rs, 80% chance of 0 Rs
2	10% chance of 450 Rs, 90% chance of 0 Rs	O	O	20% chance of **90** Rs, 80% chance of 0 Rs
3	10% chance of 450 Rs, 90% chance of 0 Rs	O	O	20% chance of **135** Rs, 80% chance of 0 Rs
4	10% chance of 450 Rs, 90% chance of 0 Rs	O	O	20% chance of **180** Rs, 80% chance of 0 Rs
5	10% chance of 450 Rs, 90% chance of 0 Rs	O	O	20% chance of **225** Rs, 80% chance of 0 Rs
6	10% chance of 450 Rs, 90% chance of 0 Rs	O	O	20% chance of **270** Rs, 80% chance of 0 Rs
7	10% chance of 450 Rs, 90% chance of 0 Rs	O	O	20% chance of **315** Rs, 80% chance of 0 Rs
8	10% chance of 450 Rs, 90% chance of 0 Rs	O	O	20% chance of **360** Rs, 80% chance of 0 Rs
9	10% chance of 450 Rs, 90% chance of 0 Rs	O	O	20% chance of **405** Rs, 80% chance of 0 Rs
10	10% chance of 450 Rs, 90% chance of 0 Rs	O	O	20% chance of **450** Rs, 80% chance of 0 Rs